In [99]:
```
# Problem 1A:
```

In [100]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import scipy.stats as stats
from statsmodels.formula.api import ols

from statsmodels.stats.anova import _get_covariance,anova_lm # For n-way ANOVA
from statsmodels.stats.multicomp import (pairwise_tukeyhsd,MultiComparison) # Tuk
import matplotlib.pyplot as plt
%matplotlib inline
```

Loading the dataset CSV file

In [101]:
```
df_salary = pd.read_csv('SalaryData.csv')
```

Checking the top 5 records

In [102]:
```
df_salary.head()
```

Out[102]:

	Education	Occupation	Salary
0	Doctorate	Adm-clerical	153197
1	Doctorate	Adm-clerical	115945
2	Doctorate	Adm-clerical	175935
3	Doctorate	Adm-clerical	220754
4	Doctorate	Sales	170769

Checking the shape and information of the dataframe

In [103]:
```
df_salary.shape
```

Out[103]:
```
(40, 3)
```

In [104]:
```
df_salary.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40 entries, 0 to 39
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Education   40 non-null     object
 1   Occupation  40 non-null     object
 2   Salary      40 non-null     int64 
dtypes: int64(1), object(2)
memory usage: 1.1+ KB
```

Checking the summary of the dataframe

In [105]:
```
df_salary.describe(include='all')
```

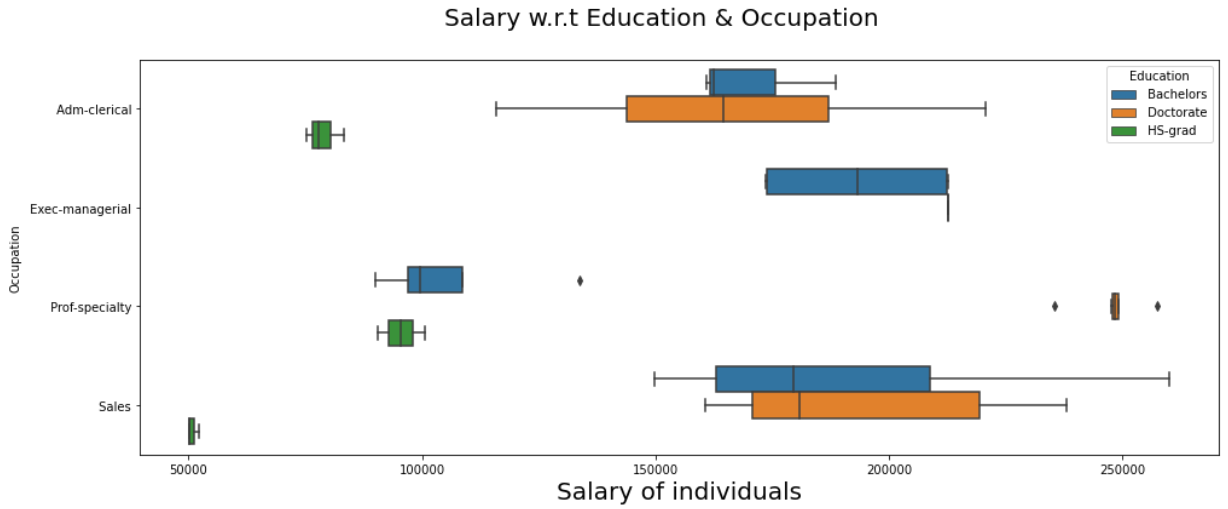
Out[105]:

	Education	Occupation	Salary
count	40	40	40.000000
unique	3	4	NaN
top	Doctorate	Prof-specialty	NaN
freq	16	13	NaN
mean	NaN	NaN	162186.875000
std	NaN	NaN	64860.407506
min	NaN	NaN	50103.000000
25%	NaN	NaN	99897.500000
50%	NaN	NaN	169100.000000
75%	NaN	NaN	214440.750000
max	NaN	NaN	260151.000000

In [106]:
```
df_salary.Occupation = pd.Categorical(df_salary.Occupation)
```

In [107]:
```
df_salary.Education = pd.Categorical(df_salary.Education)
```

In [108]:
```
fig = plt.figure(figsize=(16,6))
fig.suptitle('Salary w.r.t Education & Occupation', fontsize=20, ha='center')
sns.boxplot(x = 'Salary' , y= 'Occupation' , data = df_salary ,hue = 'Education')
plt.xlabel('Salary of individuals',fontsize=20)
plt.show();
```



Checking distinct values of Education

In [109]:
```
df_salary.Education.value_counts()
```

Out[109]:
```
 Doctorate    16
 Bachelors    15
 HS-grad       9
Name: Education, dtype: int64
```

Checking distinct values of Occupation

In [113]:
```
df_salary.Occupation.value_counts()
```

Out[113]:
```
 Prof-specialty     13
 Sales              12
 Adm-clerical       10
 Exec-managerial     5
Name: Occupation, dtype: int64
```

In [122]:
```
Doctorate = df_salary[df_salary['Education'] == ' Doctorate']['Salary']
Bachelors = df_salary[df_salary['Education'] == ' Bachelors']['Salary']
HSgrad = df_salary[df_salary['Education'] == ' HS-grad']['Salary']

ProfSpecialty = df_salary[df_salary['Occupation'] == ' Prof-specialty']['Salary']
Sales = df_salary[df_salary['Occupation'] == ' Sales']['Salary']
AdmClerical = df_salary[df_salary['Occupation'] == ' Adm-clerical']['Salary']
ExecManagerial = df_salary[df_salary['Occupation'] == ' Exec-managerial']['Salary
```

In [125]:
```
from scipy import stats
#The Shapiro-Wilk test tests the null hypothesis that the data was drawn from a r
#alpha = 0.05
print(stats.shapiro([Doctorate]))
print(stats.shapiro([Bachelors]))
print(stats.shapiro([HSgrad]))

print(stats.shapiro([ProfSpecialty]))
print(stats.shapiro([Sales]))
print(stats.shapiro([AdmClerical]))
print(stats.shapiro([ExecManagerial]))
```

```
ShapiroResult(statistic=0.8952829837799072, pvalue=0.0675690770149231)
ShapiroResult(statistic=0.9607304334640503, pvalue=0.7050924301147461)
ShapiroResult(statistic=0.885286271572113, pvalue=0.1783432960510254)
ShapiroResult(statistic=0.736305832862854, pvalue=0.0013131146552041173)
ShapiroResult(statistic=0.8897126913070679, pvalue=0.11683900654315948)
ShapiroResult(statistic=0.9189430475234985, pvalue=0.34822404384613037)
ShapiroResult(statistic=0.6901877522468567, pvalue=0.007539781276136637)
```

In [126]:
```
#Anderson Darling Test if Shapiro fails
print(stats.anderson(Doctorate,dist='norm'))
print(stats.anderson(Bachelors,dist='norm'))
print(stats.anderson(HSgrad,dist='norm'))


print(stats.anderson(ProfSpecialty,dist='norm'))
print(stats.anderson(Sales,dist='norm'))
print(stats.anderson(AdmClerical,dist='norm'))
print(stats.anderson(ExecManagerial,dist='norm'))
# if statistic < critical_values then data looks normal (fail to reject H0)
```

```
AndersonResult(statistic=0.6725735337482739, critical_values=array([0.5  , 0.56
9, 0.683, 0.797, 0.948]), significance_level=array([15. , 10. ,  5. ,  2.5,  1.
]))
AndersonResult(statistic=0.2793685121409055, critical_values=array([0.498, 0.56
8, 0.681, 0.794, 0.945]), significance_level=array([15. , 10. ,  5. ,  2.5,  1.
]))
AndersonResult(statistic=0.4369535315712767, critical_values=array([0.507, 0.57
8, 0.693, 0.808, 0.961]), significance_level=array([15. , 10. ,  5. ,  2.5,  1.
]))
AndersonResult(statistic=1.5424424719265737, critical_values=array([0.497, 0.56
6, 0.679, 0.792, 0.942]), significance_level=array([15. , 10. ,  5. ,  2.5,  1.
]))
AndersonResult(statistic=0.5755046432785171, critical_values=array([0.497, 0.56
6, 0.679, 0.792, 0.942]), significance_level=array([15. , 10. ,  5. ,  2.5,  1.
]))
AndersonResult(statistic=0.3783000997297936, critical_values=array([0.501, 0.57
, 0.684, 0.798, 0.95 ]), significance_level=array([15. , 10. ,  5. ,  2.5,  1.
]))
AndersonResult(statistic=0.7842030726712084, critical_values=array([0.72 , 0.82
, 0.984, 1.148, 1.365]), significance_level=array([15. , 10. ,  5. ,  2.5,  1.
]))
```

In [127]:
```
#Homogeniety
#The Levene test tests the null hypothesis that all input samples are from popul
#alpha = 0.05
print(stats.levene(Doctorate,Bachelors,HSgrad))
print(stats.levene(ProfSpecialty,Sales,AdmClerical,ExecManagerial))
```

```
LeveneResult(statistic=1.8800921605836554, pvalue=0.16686425699301183)
LeveneResult(statistic=2.4378177404396832, pvalue=0.0803790714975064)
```

Formulate the Null and Alternate Hypothesis

Null Hypothesis H_0 : The mean salary earned by an individual is same with different categories of Education qualification

Alternate Hypothesis H_A : The mean salary earned by an individual is different in at-least one category of Education qualification

One Way Anova : Education

In [128]:
```
formula = 'Salary ~ C(Education)'
model = ols(formula, df_salary).fit()
aov_table = anova_lm(model)
print(aov_table)
```

```
                df        sum_sq       mean_sq          F        PR(>F)
C(Education)   2.0  1.026955e+11  5.134773e+10  30.95628  1.257709e-08
Residual      37.0  6.137256e+10  1.658718e+09        NaN           NaN
```

In [129]:
```
f,p = stats.f_oneway(df_salary[df_salary['Education'] == ' Doctorate'].Salary , d
```

In [130]:
```
print(p)
```

```
1.2577090926629002e-08
```

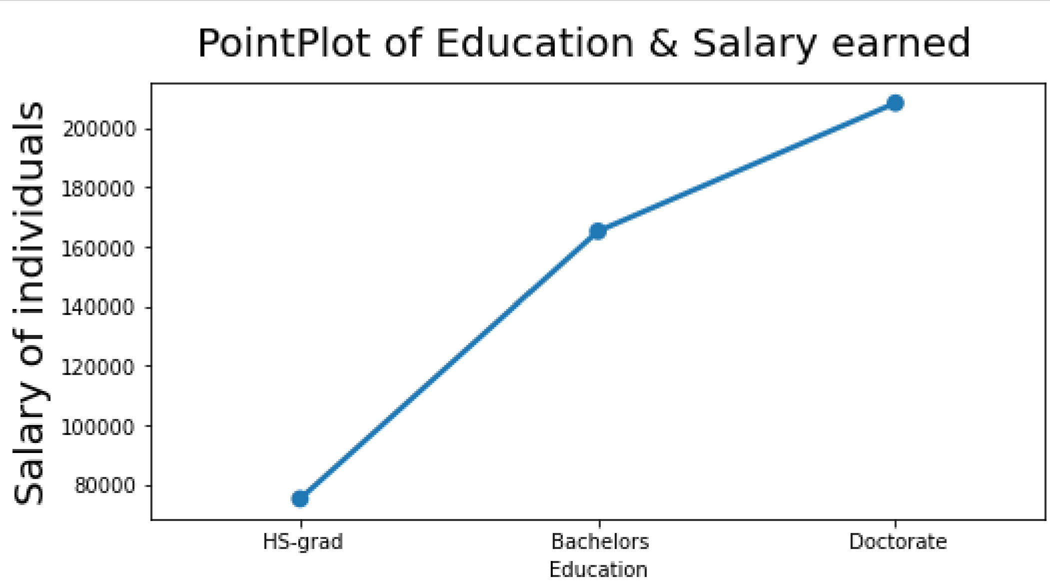
In [131]:
```
print(f)
```

```
30.95628008792558
```

Now, we see that the corresponding p-value is less than alpha (0.05). Thus, we reject the Null Hypothesis (H_0).

Conclusion: Since the p value is less than the significance level (0.05), we can reject the null hypothesis and conclude that the mean salary earned by an individual is different in at-least one category of Education qualifications

In [132]:
```
fig = plt.figure(figsize=(8,4))
fig.suptitle('PointPlot of Education & Salary earned', fontsize=20, ha='center')
sns.pointplot(x= 'Education',y = 'Salary',data = df_salary, order=[' HS-grad',' B
plt.ylabel('Salary of individuals',fontsize=20)
plt.show();
```



Tukey HSD (Honestly Significant Difference) Test

single-step multiple comparison procedure and statistical test

In [133]:
```
mc = MultiComparison( df_salary['Salary'], df_salary['Education'])
result = mc.tukeyhsd()
print(result)
```

```
           Multiple Comparison of Means - Tukey HSD, FWER=0.05
=========================================================================
  group1     group2     meandiff   p-adj     lower        upper    reject
-------------------------------------------------------------------------
 Bachelors  Doctorate   43274.0667 0.0146    7541.1439  79006.9894   True
 Bachelors    HS-grad  -90114.1556  0.001 -132035.1958 -48193.1153   True
 Doctorate    HS-grad -133388.2222  0.001 -174815.0876 -91961.3569   True
-------------------------------------------------------------------------
```

Doctorate - Bachelors = 43274.0667

HS-grad - Bachelors = -90114.1556

HS-grad - Doctorate = -133388.2222

Hence, Doctorate > Bachelors > HS-grad

The above results reveal that the means of 3 categories of Education qualifications differ from each other

One Way Anova : Occupation

In [134]:
```
formula = 'Salary ~ C(Occupation)'
model = ols(formula, df_salary).fit()
aov_table = anova_lm(model)
print(aov_table)
```

```
                 df        sum_sq       mean_sq         F    PR(>F)
C(Occupation)   3.0  1.125878e+10  3.752928e+09  0.884144  0.458508
Residual       36.0  1.528092e+11  4.244701e+09       NaN       NaN
```

In [135]:
```
f,p = stats.f_oneway(df_salary[df_salary['Occupation'] == ' Prof-specialty'].Sala
```

In [136]:
```
print(p)
```

```
0.4585078266495116
```

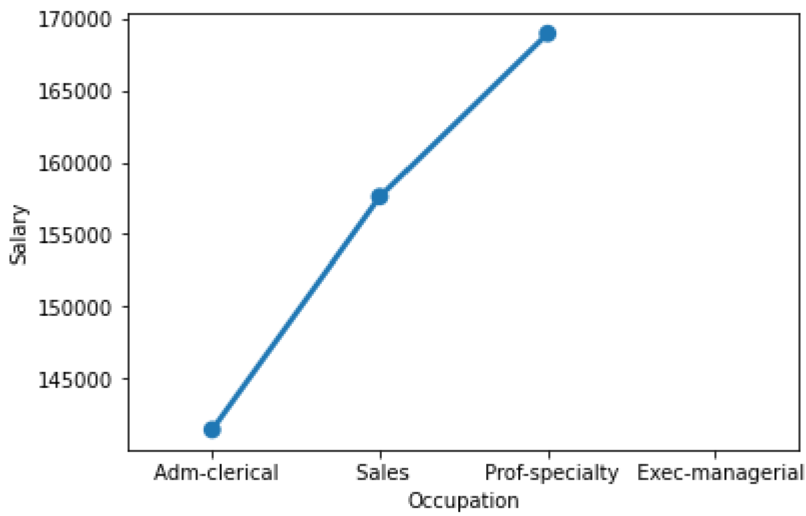
In [137]:
```
print(f)
```

```
0.8841441289216039
```

Conclusion: Since the p value is more than the significance level (0.05), we can accept the null hypothesis and conclude that the mean salary earned by an individual is same with different categories of Occupation

In [138]:
```
sns.pointplot(x = 'Occupation',y = 'Salary' ,data = df_salary, order=[' Adm-cleri
```

Out[138]:
```
<AxesSubplot:xlabel='Occupation', ylabel='Salary'>
```



Tukey HSD (Honestly Significant Difference) Test

single-step multiple comparison procedure and statistical test

In [139]:
```
mc = MultiComparison( df_salary['Salary'], df_salary['Occupation'])
result = mc.tukeyhsd()
print(result)
```

```
                Multiple Comparison of Means - Tukey HSD, FWER=0.05
================================================================================
=====
     group1           group2        meandiff  p-adj     lower        upper    r
eject
--------------------------------------------------------------------------------
-----
    Adm-clerical  Exec-managerial     55693.3 0.4146  -40415.1459 151801.7459
False
    Adm-clerical   Prof-specialty  27528.8538 0.7252  -46277.4011 101335.1088
False
    Adm-clerical            Sales  16180.1167    0.9  -58951.3115  91311.5449
False
 Exec-managerial   Prof-specialty -28164.4462 0.8263 -120502.4542  64173.5618
False
 Exec-managerial            Sales -39513.1833 0.6507 -132913.8041  53887.4374
False
  Prof-specialty            Sales -11348.7372    0.9  -81592.6398  58895.1655
False
--------------------------------------------------------------------------------
-----
```

Exec-managerial - Adm-clerical = 55693.3

Prof-specialty - Adm-clerical = 27528.8538

Sales - Adm-clerical = 16180.1167

Prof-specialty - Exec-managerial = -28164.4462

Sales - Exec-managerial = -39513.1833

Sales - Prof-specialty = -11348.7372

Hence, Exec-managerial > Prof-specialty > Sales > Adm-clerical

The above results reveal that the means of 3 categories of Occupations differ from each other

In [140]:
```
# Problem 1B:
```

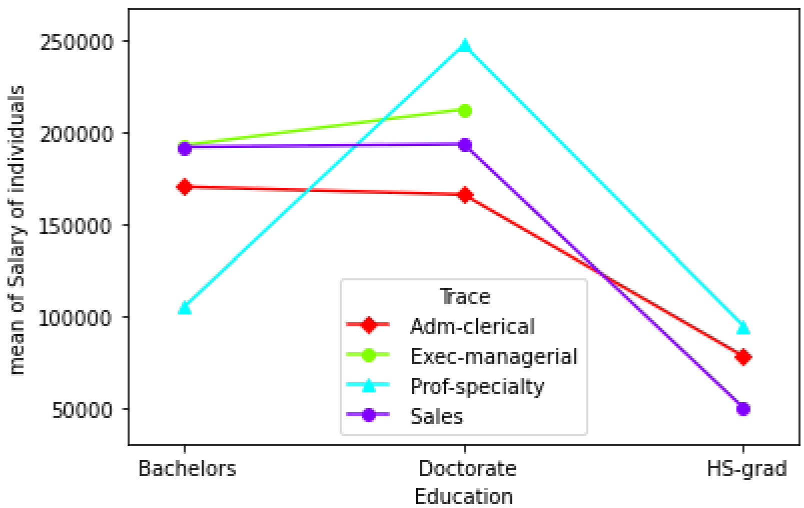
Two Way Anova : Education & Occupation

In [141]:
```
formula = 'Salary ~ C(Education) + C(Occupation)'
model = ols(formula, df_salary).fit()
aov_table = anova_lm(model)
print(aov_table)
```

```
                  df        sum_sq       mean_sq          F        PR(>F)
C(Education)     2.0  1.026955e+11  5.134773e+10  31.257677  1.981539e-08
C(Occupation)    3.0  5.519946e+09  1.839982e+09   1.120080  3.545825e-01
Residual        34.0  5.585261e+10  1.642724e+09        NaN           NaN
```

In [144]:
```
from statsmodels.graphics.factorplots import interaction_plot

interaction_plot(x = np.array(df_salary['Education']),trace = np.array(df_salary|
plt.show();
```



Still, we can see that there is some sort of interaction between the two treatments. So, we will introduce a new term while performing the Two Way ANOVA.

Two Way Anova : Education & Occupation with Interaction

In [43]:
```
formula = 'Salary ~ C(Education) +C(Occupation)+  C(Education):C(Occupation)'
model = ols(formula, df_salary).fit()
aov_table = anova_lm(model,type=1)
print(aov_table)
```

```
                              df        sum_sq       mean_sq          F  \
C(Education)                 2.0  1.026955e+11  5.134773e+10  72.211958   
C(Occupation)                3.0  5.519946e+09  1.839982e+09   2.587626   
C(Education):C(Occupation)   6.0  3.634909e+10  6.058182e+09   8.519815   
Residual                    29.0  2.062102e+10  7.110697e+08        NaN   

                                  PR(>F)  
C(Education)                5.466264e-12  
C(Occupation)               7.211580e-02  
C(Education):C(Occupation)  2.232500e-05  
Residual                             NaN  
```

Due to the inclusion of the interaction effect term, we can see a slight change in the p-value of the first two treatments as compared to the Two-Way ANOVA without the interaction effect terms.And we see that the p-value of the interaction effect term of 'Education' and 'Occupation' suggests that the Null Hypothesis is rejected in this case.

In [145]:
```
model.summary()
```

Out[145]:

OLS Regression Results

Dep. Variable:	Salary	**R-squared:**	0.660
Model:	OLS	**Adj. R-squared:**	0.610
Method:	Least Squares	**F-statistic:**	13.18
Date:	Fri, 14 May 2021	**Prob (F-statistic):**	3.63e-07
Time:	22:55:56	**Log-Likelihood:**	-477.90
No. Observations:	40	**AIC:**	967.8
Df Residuals:	34	**BIC:**	977.9
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.461e+05	1.62e+04	9.028	0.000	1.13e+05	1.79e+05
C(Education)[T. Doctorate]	4.912e+04	1.52e+04	3.238	0.003	1.83e+04	7.99e+04
C(Education)[T. HS-grad]	-8.115e+04	1.8e+04	-4.515	0.000	-1.18e+05	-4.46e+04
C(Occupation)[T. Exec-managerial]	4.117e+04	2.34e+04	1.760	0.087	-6358.221	8.87e+04
C(Occupation)[T. Prof-specialty]	1.889e+04	1.71e+04	1.106	0.277	-1.58e+04	5.36e+04
C(Occupation)[T. Sales]	1.13e+04	1.74e+04	0.651	0.520	-2.4e+04	4.66e+04

Omnibus:	0.637	**Durbin-Watson:**	1.353
Prob(Omnibus):	0.727	**Jarque-Bera (JB):**	0.153
Skew:	-0.123	**Prob(JB):**	0.926
Kurtosis:	3.177	**Cond. No.**	5.94

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.